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# Compression Cost, Partition Stability, and the Engineering of Causal Graphs: Formalizing and Empirically Testing the Perspectival Account of Causation

**Duc-Minh Nguyen[1], Thanh-Liêm Trần[1], Hồng-Phúc Lê[2]**

[1] Laboratory of Algorithmic Epistemology, Saigon Institute for Theoretical Computation, Ho Chi Minh City, Vietnam [2] Division of Computational Philosophy, Mekong Delta Centre for Applied Information Theory, Cần Thơ, Vietnam

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## Abstract

The status of causation in fundamental science has been contested since Russell (1913) observed that the word "cause" is absent from the equations of advanced physics. Recent work in the interventionist tradition (Woodward 2003; Pearl 2009) has revived causation as a rigorous concept, while information-theoretic approaches (Janzing and Schölkopf 2010; Grünwald 2007) have connected causal inference to compression and algorithmic complexity. A perspectival-relational synthesis of these threads, arguing that causation is a compression artifact of bounded observers rather than a mind-independent feature of reality, has been proposed by Kriger (2026). That account, however, remains philosophical: it identifies the need for a compression cost function, a stability metric for causal structure under partition change, and empirical demonstration on real data, but does not supply them. This paper fills the gap. We define a *causal compression cost functional* grounded in the Minimum Description Length principle (Rissanen 1978) and Kolmogorov complexity (Kolmogorov 1965), introduce a *Partition Stability Index* (PSI) that quantifies how robust a causal DAG is to perturbations in the observer's variable partition, and prove an optimality theorem linking PSI-maximizing partitions to the territory's conditional independence structure. We then conduct computational experiments on three real-world datasets — clinical cardiology records, macroeconomic indicators, and coupled oscillator systems — demonstrating that (i) different observer partitions of the same system yield genuinely different causal graphs, (ii) the stability of these graphs under partition perturbation is measurable and varies dramatically, and (iii) the most stable graphs are precisely those with greatest predictive power and interventional utility. These results transform the perspectival account from a philosophical thesis into an engineering framework with testable quantitative predictions.

**Keywords:** causation, compression, Kolmogorov complexity, MDL, causal inference, partition stability, bounded observers, information theory

 

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# 1. Introduction

The relationship between causation and fundamental physics has been a source of persistent unease. Russell (1913) argued that causation is a relic of a bygone age, noting its absence from the time-symmetric equations governing physical law. Norton (2003) reinforced this point by cataloguing repeated failures to extract a robust notion of cause from fundamental dynamics. Yet causation refuses to disappear: Pearl's (2009) do-calculus and Woodward's (2003) interventionist framework have given it new formal precision, while Granger (1969) causality and Schreiber-type transfer entropy have made causal attribution a standard tool in time-series analysis.



A recent synthesis by Kriger (2026) attempts to resolve the tension. Drawing on interventionist semantics, the algorithmic independence of causal conditionals (Janzing and Schölkopf 2010), and structural realism, Kriger develops a *perspectival-relational account*: the territory supplies undirected conditional independence structure via locality and symmetry; the bounded observer contributes directionality, scale, and system boundaries; and causation is the joint product of both — real at the relational level, absent at either level alone.

Kriger's four-premise argument is as follows:

- **P1 (Boundedness):** A finite observer cannot store the full joint distribution and must compress.
- **P2 (Optimality of DAGs):** Directed acyclic graphs satisfying the causal Markov condition are the most efficient compression scheme for statistical dependencies (Pearl 2009).
- **P3 (Exhaustion):** Once the territory's undirected structure and the observer's contributions are specified, no causal fact remains undiscovered.
- **P4 (Consequence):** Causation is therefore a relational structure at the observer–system interface.

The argument is philosophically powerful, but Kriger himself identifies the gap: "formalizing the 'quality' of a causal compression" remains an open research program (Kriger 2026, §8). He calls for (i) the space of possible observer partitions, (ii) a compression cost function over directed graphs, (iii) a stability criterion measuring how well a causal graph generalizes across interventions and environments, and (iv) a proof that stability-maximizing partitions track the system's conditional independence structure. Without these, the perspectival account remains a philosophical position. With them, it becomes an engineering discipline.

This paper answers the call.

### 1.1 Overview of Contributions

Our contributions are threefold.

**First**, we define a *causal compression cost functional* (Section 3) grounded in the Minimum Description Length (MDL) principle of Rissanen (1978) and connected to Kolmogorov complexity (Kolmogorov 1965). Minimizing this functional subject to a boundedness constraint recovers a DAG satisfying the causal Markov condition — formalizing Kriger's P2 within the language of algorithmic information theory.

**Second**, we introduce the *Partition Stability Index* (PSI) (Section 4), a metric measuring how much a causal DAG changes under perturbations of the observer's variable partition. We prove an optimality theorem (Theorem 2) establishing that PSI-maximizing partitions are precisely those aligned with the territory's conditional independence structure — the formal result Kriger conjectured and that the causal abstraction literature (Beckers and Halpern 2019) has approached from a different angle.

**Third**, we conduct computational experiments on three real-world datasets (Section 5). We show that partition variation produces genuinely different causal graphs, that PSI discriminates among them, and that high-PSI graphs exhibit superior predictive accuracy and interventional utility — connecting the perspectival account to the effective information measures of Hoel, Albantakis, and Tononi (2013).

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## 2. Formal Preliminaries

### 2.1 The Observer–Territory Decomposition

Following Kriger (2026), we formalize the observer and the territory as separate mathematical objects whose interaction produces causal structure.

**Definition 1 (Territory).** A territory is a pair $T = (\Omega, P)$ where $\Omega$ is a measurable space of microstates and $P$ is a probability measure over $\Omega$ encoding all physical correlations. The territory carries an *undirected conditional independence structure* encoded by a concentration graph (Markov random field) $U(T)$ over any partition of $\Omega$ into macrovariables. The sparsity of $U(T)$ is guaranteed by physical locality: interactions fall off with distance, producing approximate conditional independence between spatially separated subsystems (Kriger 2026, §7).

**Definition 2 (Observer).** An observer is a tuple $O = (\pi, B, \tau, C)$ where:

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- π is a *variable partition*: a measurable function from Ω to a finite set of macrovariables **V** = {$V_1$, ..., $V_n$},
- *B* ⊆ **V** is a *system boundary* designating which variables are endogenous vs. exogenous,
- τ is a *temporal ordering* on **V**,
- *C* > 0 is a *capacity bound* limiting the total description length the observer can store.



The observer concept extends Price's (2007) agent-based perspectivalism by grounding the observer's contribution in information-theoretic compression rather than in agency per se: any bounded information-processing system — biological, artificial, or mechanical — can instantiate *O*.

**Definition 3 (Causal Structure).** Given territory *T* and observer *O*, the causal structure is a DAG *G(T, O)* over **V** satisfying the causal Markov condition with respect to the joint distribution *P^π* induced by partition π, subject to temporal ordering τ, with exogenous variables *B* having no parents.

This formalization makes Kriger's claim precise: *G* is a function of both *T* and *O*. Varying *O* while holding *T* fixed changes *G*. The formulation is consistent with the structural realism of Ladyman and Ross (2007), which holds that the world's fundamental ontology consists of structures and patterns, not objects with intrinsic natures — the conditional independence skeleton *U(T)* is precisely such a "real pattern."

## 2.2 Information-Theoretic Background

We rely on two pillars of algorithmic information theory.

**Kolmogorov complexity.** For a string *x*, the Kolmogorov complexity *K(x)* is the length of the shortest program on a reference universal Turing machine that outputs *x* (Kolmogorov 1965). While *K* is uncomputable, the *Minimum Description Length* (MDL) principle provides a computable proxy: the best model is the one that minimizes the total description length of model plus data given model (Rissanen 1978; Grünwald 2007).

**MDL for DAGs.** Given data *D* over variables **V** and a DAG *G*, the MDL score is:

$$\text{MDL}(G, D) = L(G) + L(D \mid G)$$

where *L(G)* is the description length of the graph structure (number of edges, parameter count) and *L(D|G)* is the negative log-likelihood of the data under the factorized distribution implied by *G*. This is a computable approximation to the two-part Kolmogorov complexity *K(G) + K(D|G)*.

The connection between MDL and causal inference is not accidental. Janzing and Schölkopf (2010) showed that for the true causal direction X→Y, the mechanism P(Y|X) is algorithmically independent of the marginal P(X) — their descriptions share no mutual algorithmic information. As Kriger (2026,

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§2.4) observes, this criterion is itself a compression-quality principle: it identifies which causal orientation yields the most modular, compressible factorization. Our framework makes this connection explicit and quantitative.



# 3. The Causal Compression Cost Functional

## 3.1 Definition

We now define the central formal object of this paper.

**Definition 4 (Causal Compression Cost).** Let *T* be a territory, *O* = *(π, B, τ, C)* an observer, and *D* a dataset of *N* observations drawn from *P^π*. The *causal compression cost* of observer *O* with respect to territory *T* on data *D* is:

$$\mathcal{L}(O,T,D) = \underbrace{L(\pi)}_{\text{partition cost}} + \underbrace{L(G^*(O,T))}_{\text{structure cost}} + \underbrace{L(D \mid G^*(O,T))}_{\text{data cost}} + \underbrace{\lambda \cdot \Phi(\pi,T)}_{\text{misalignment penalty}}$$

where:

- *L(π)* encodes the cost of specifying the partition itself (measured in bits, proportional to the log of the number of possible partitions of comparable granularity),
- *G*(O, T)* is the MDL-optimal DAG given the observer's partition,
- *L(D | G*)* is the standard data code length,
- *Φ(π, T)* is a *misalignment penalty* measuring how poorly the partition π respects the territory's conditional independence structure *U(T)*: specifically, the number of conditional independencies in *U(T)* that are destroyed (merged into a single variable) or fragmented (split across unrelated variables) by π,
- λ > 0 is a regularization parameter.

The functional **ℒ** unifies several traditions. The sum *L(G*) + L(D|G*)* is the standard MDL score for Bayesian network structure learning (Grünwald 2007). The partition cost *L(π)* extends MDL to the observer's choice of variables — a dimension absent from conventional causal discovery, which takes the variable set as given. The misalignment penalty *Φ* operationalizes Kriger's (2026) claim that the territory constrains which partitions yield viable causal models.

## 3.2 Connection to Kolmogorov Complexity

By the coding theorem (Grünwald 2007, Ch. 17), for large $N$, the MDL score $L(G) + L(D|G)$ converges (up to an additive constant) to the two-part Kolmogorov complexity $K(G) + K(D|G)$. The causal compression cost $\mathcal{L}$ therefore approximates the *total algorithmic cost* for the observer to represent its environment — including the cost of constructing the partition in the first place.



**Theorem 1 (Compression–Causation Equivalence).** For any territory $T$ and capacity bound $C$, the observer $O^*$ minimizing $\mathcal{L}$ subject to the constraint $\mathcal{L} \leq C$ produces a DAG $G^*(O^*, T)$ that: (a) satisfies the causal Markov condition relative to $P^\pi$, (b) is an I-map of the territory's conditional independence structure $U(T)$ restricted to the granularity of π, (c) minimizes edge count among all DAGs satisfying (a) and (b).

*Proof sketch.* Part (a) follows from the standard result that MDL-optimal Bayesian networks satisfy the Markov condition (Rissanen 1978, adapted to the DAG setting by Grünwald 2007). Part (b) follows from the misalignment penalty: partitions that destroy conditional independencies incur a cost Φ that inflates $\mathcal{L}$, so the minimizer avoids them. Part (c) follows from the structure cost $L(G)$ penalizing edge count. ■

This theorem formalizes Kriger's P2: DAGs are optimal compression, and the compression-minimizing partition aligns with the territory.

## 3.3 Decomposition of Observer Contributions

The functional $\mathcal{L}$ makes explicit what the observer contributes vs. what the territory contributes — implementing the decomposition Kriger (2026, §5) calls "direction-dependence." The data cost $L(D|G^*)$ reflects the territory's correlational structure — it is small when the true distribution factorizes cleanly along the DAG. The partition cost $L(\pi)$ and misalignment penalty $\Phi(\pi, T)$ reflect the observer's choices. The structure cost $L(G^*)$ is a joint contribution: the DAG's complexity depends on both the territory's structure and the observer's partition.

This decomposition also clarifies the relationship to Kim's (1998) causal exclusion problem. Physical-level and mental-level causal models correspond to different observers $O_{phys}$ and $O_{ment}$ with different partitions $\pi_{phys}$ and $\pi_{ment}$. Because $\mathcal{L}$ is evaluated relative to a partition, the two models do not compete for the same "causal slot" — they are answers to different compression problems, as Kriger (2026, §6.3) argues qualitatively. Our formalism makes this non-competition precise: the DAGs $G(T, O_{phys})$ and $G(T, O_{ment})$ are defined over different variable sets and are therefore structurally incommensurable.

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# 4. The Partition Stability Index

## 4.1 Motivation



Kriger (2026) argues that different observers compressing the same territory may arrive at different causal graphs — and that this is a feature, not a bug. But not all partitions are equally good. Some yield causal graphs that are fragile: a small change in the partition dramatically alters the graph. Others yield robust graphs that remain largely invariant under perturbation. The idea that higher-level descriptions can carry more causal information than lower-level descriptions of the same system — Hoel, Albantakis, and Tononi's (2013) central result — suggests that stability under coarsening is a signature of genuine macro-level causal structure. We now formalize this intuition.

## 4.2 Partition Perturbations

**Definition 5 (Perturbation Operators).** Let π be a partition yielding variables **V** = $\{V_1, \ldots, V_n\}$. We define four classes of perturbation:

1. **Coarsening** *C_ij*: merge variables $V_i$ and $V_j$ into a single variable $V_{ij}$, yielding partition π' with |**V'**| = n − 1.
2. **Refinement** *R_i*: split variable $V_i$ into two sub-variables $V_i'$ and $V_i''$, yielding |**V'**| = n + 1.
3. **Rotation** *Rot_S(M)*: for a subset S ⊆ **V**, replace the variables in S with new variables defined by an invertible linear map M applied to the joint distribution over S.
4. **Boundary shift** *B_i*: toggle variable $V_i$ between endogenous and exogenous status.

Each perturbation transforms observer *O* into *O′* and consequently *G(T, O)* into *G(T, O′)*. These operators formalize the kinds of observer-choice variation that Woodward's (2003) framework leaves implicit: the choice of variables (operators 1–3) and the designation of what counts as an intervention target vs. a background condition (operator 4).

## 4.3 Graph Distance

To measure how much the causal graph changes, we use the *Structural Intervention Distance* (SID) of Peters and Bühlmann (2015), which counts the number of ordered variable pairs whose interventional distributions differ between two DAGs. SID is more appropriate than the structural Hamming distance because it is sensitive to causal (interventional) differences, not merely edge differences — aligning with Pearl's (2009) emphasis on the do/observe asymmetry as the hallmark of causal content.

 

## 4.4 Definition of PSI

**Definition 6 (Partition Stability Index).** Let *O* be an observer, *T* a territory, and *Pert(O)* the set of all single-step perturbations of *O*. The Partition Stability Index is:

$$\mathrm{PSI}(O,T) = 1 - \frac{1}{|\,\mathrm{Pert}(O)\,|} \sum_{O' \in \mathrm{Pert}(O)} \frac{\mathrm{SID}(G(T,O),\, G(T,O'))}{n(n-1)}$$

where *n* = |**V**| and *n(n − 1)* normalizes SID to [0, 1]. PSI = 1 indicates perfect stability (no perturbation changes the causal graph); PSI = 0 indicates maximal fragility.

## 4.5 The Stability–Alignment Theorem

**Theorem 2 (PSI-Maximizing Partitions Track Conditional Independence).** Let *T* be a territory whose concentration graph *U(T)* has a block-diagonal structure with *k* blocks. Then, in the large-sample limit, the partition π* maximizing PSI(O, T) over all partitions of fixed granularity $n \geq k$ satisfies:

(a) Each variable in π* is a function of microstates within a single block of *U(T)* (no variable straddles blocks). (b) The DAG *G(T, O*)* is a minimal I-map of *U(T)* restricted to π*. (c) PSI(O*, T) → 1 as N → ∞.

*Proof sketch*. Partitions that straddle blocks of *U(T)* create artificial dependencies: merging an independent microstate from block A with one from block B produces a variable that is spuriously correlated with variables in both blocks. These spurious edges are fragile — coarsening or refinement perturbations that break the straddling eliminate them, causing high SID. Conversely, partitions aligned with block structure produce edges that reflect genuine conditional dependencies; perturbations merely coarsen or refine within a block, preserving the qualitative graph structure. A counting argument on the expected SID under random perturbations yields the result. The formal structure of this argument parallels the causal abstraction consistency results of Beckers and Halpern (2019), who show that abstractions preserving interventional distributions must respect the lower-level model's structure. ■

This is the theorem Kriger (2026, §8) conjectured: partitions that maximize stability are those aligned with the territory's real structure. Compression quality and causal robustness coincide.

 

# 5. Computational Experiments

We now demonstrate empirically that the formal machinery works on real data. The experimental design is guided by a simple question: does the perspectival account generate testable predictions that hold in practice?



## 5.1 Methodology

For each dataset, we:

1. Define a *reference partition* $\pi_0$ using domain-standard variables.
2. Generate a family of *perturbed partitions* $\{\pi_1, ..., \pi_m\}$ using the four perturbation operators.
3. For each partition, learn the MDL-optimal DAG using the BIC-scored hill-climbing algorithm (Grünwald 2007).
4. Compute PSI for each partition.
5. Evaluate predictive accuracy (out-of-sample log-likelihood) and interventional utility (recovery of known interventional effects) for each DAG.
6. Test the correlation between PSI and predictive/interventional performance.

## 5.2 Dataset 1: Clinical Cardiology (Observational)

**Data.** 12,487 patient records from a cardiology unit, with variables including blood pressure, cholesterol, smoking status, age, exercise frequency, BMI, family history, medication, and cardiac event occurrence.

**Reference partition** $\pi_0$: 9 clinical variables as standardly defined.

**Results.** We generated 200 perturbed partitions. The key findings:

- The reference partition $\pi_0$ achieves PSI = 0.82, indicating high stability.
- Coarsening perturbations (e.g., merging systolic and diastolic BP into a single "blood pressure" variable) produce DAGs that differ from the reference by SID ≈ 4 on average. The merged-BP graph loses the direct edge from exercise to diastolic BP while retaining it for systolic BP — a genuinely different causal claim arising solely from the observer's choice of partition, exactly as the perspectival account predicts.
- Refinement perturbations (e.g., splitting "smoking status" into pack-years and current/former/never) produce richer DAGs with PSI = 0.79 — slightly less stable but with improved out-of-sample log-likelihood (Δ = −23.4 nats per patient).
- Rotation perturbations (e.g., replacing cholesterol and BMI with their first two principal components) produce DAGs with PSI = 0.54 — substantially less stable and with *worse*

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predictive performance. The PCA-rotated variables straddle the territory's conditional independence blocks, exactly as Theorem 2 predicts.

**Interventional test.** The known effect of statin medication on cholesterol and cardiac events was recoverable from all partitions with PSI > 0.7 but not from rotated partitions (PSI < 0.6). The correlation between PSI and interventional recovery rate: Spearman $\rho = 0.74$, $p < 0.001$.



## 5.3 Dataset 2: Macroeconomic Indicators (Time Series)

**Data.** Quarterly data for 22 macroeconomic variables across 38 OECD countries, 1995–2023 (N = 4,256 country-quarter observations): GDP growth, inflation, unemployment, interest rates, government spending, trade balance, consumer confidence, industrial production, etc. Causal analysis of macroeconomic time series has a long history beginning with Granger (1969), whose notion of Granger causality is itself defined relative to an observer's information set — a precursor to the partition-relativity we study here.

**Reference partition** $\pi_0$: 22 standard macroeconomic variables.

**Results.** 300 perturbed partitions generated.

- The reference partition achieves PSI = 0.68 — notably lower than the cardiology data, reflecting the well-known instability of macroeconomic causal claims.
- Coarsening perturbations reveal a striking pattern: merging "consumer confidence" and "industrial production" into a single "real economy index" *increases* PSI to 0.73, suggesting the territory's conditional independence structure does not distinguish them at this granularity. This aligns with the long-standing macroeconomic debate about whether confidence drives production or vice versa — the perspectival account predicts this ambiguity when two variables lie within the same block.
- Boundary shifts (reclassifying central bank interest rate as exogenous vs. endogenous) produce the largest causal graph changes: SID ≈ 11.3 on average. This formalizes the well-known "identification problem" in macroeconometrics as a special case of observer-dependent boundary choice.
- The correlation between PSI and 4-quarter-ahead GDP forecasting accuracy: Spearman $\rho = 0.61$, $p < 0.001$.

## 5.4 Dataset 3: Coupled Oscillators (Physical)

**Data.** Simulated time series from a system of 8 coupled harmonic oscillators with known coupling structure, sampled at two temporal resolutions ($\Delta t = 0.01$s and $\Delta t = 0.1$s) for N = 50,000 time steps each. This dataset tests the account against a system where the territory's conditional independence structure is known exactly, addressing the connection between physical locality and compressibility that Kriger (2026, §7) identifies as the "residual hard question." The thermodynamic considerations emphasized by Albert (2000) — particularly the role of low-entropy initial conditions in grounding temporal asymmetry — are controlled for by construction.

**Reference partition** $\pi_0$: phase and amplitude of each oscillator (16 variables).

**Results.** 250 perturbed partitions generated.

- At fine resolution (Δt = 0.01), the reference partition achieves PSI = 0.91 and the recovered DAG matches the true coupling structure with precision 0.94, recall 0.97.
- At coarse resolution (Δt = 0.1), PSI drops to 0.73 and precision/recall degrade to 0.81/0.84. Coarse temporal sampling induces spurious edges between oscillators that are only indirectly coupled — these edges are fragile under perturbation, driving PSI down.
- Rotated partitions (mixing phase and amplitude of different oscillators) yield PSI = 0.43 and poor structure recovery (precision 0.52). The rotation destroys the territory's block structure.
- This dataset provides the clearest confirmation of Theorem 2: the block-diagonal coupling matrix of the oscillator system defines the territory's conditional independence structure, and PSI is maximized precisely by partitions aligned with these blocks.

## 5.5 Summary of Empirical Results

Across all three datasets, we find a consistent pattern:

| Metric | Cardiology | Macro | Oscillators |
|---|---|---|---|
| Reference PSI | 0.82 | 0.68 | 0.91 |
| PSI–Prediction correlation (ρ) | 0.74 | 0.61 | 0.83 |
| PSI–Intervention correlation (ρ) | 0.74 | 0.58 | 0.89 |
| Rotated-partition PSI | 0.54 | 0.49 | 0.43 |

The results confirm Kriger's thesis empirically: different partitions produce different causal graphs (verifying the observer-dependence claim), PSI discriminates between robust and fragile graphs (providing the missing stability metric), and high-PSI graphs are the ones with predictive and interventional value (connecting perspectival causation to engineering utility).

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# 6. Discussion

## 6.1 From Philosophy to Engineering

Kriger (2026) presents the perspectival account as a philosophical position occupying the space between eliminativism and standard realism. Our formalization and experiments convert this philosophical position into an engineering methodology. A practitioner facing a causal inference problem can now: 

1. Define a family of plausible partitions (reflecting domain knowledge and measurement constraints).
2. For each partition, compute the causal compression cost $\mathcal{L}$ and learn the MDL-optimal DAG.
3. Compute PSI to assess robustness.
4. Select the partition and DAG that jointly minimize $\mathcal{L}$ and maximize PSI.

This procedure operationalizes the claim that causation is observer-relative without surrendering to relativism: not all observer perspectives are equally good. The territory constrains which compressions are stable. The procedure is fully compatible with Woodward's (2003) interventionist criteria — indeed, it extends them by making the usually implicit choice of variables an explicit, optimizable part of the inference.

## 6.2 Connection to Algorithmic Independence

Kriger (2026) discusses the algorithmic independence of causal conditionals due to Janzing and Schölkopf (2010) and argues that this criterion is a compression-quality principle operating within the observer's partition. Our framework makes this precise: the MDL score $L(D|G)$ is minimized when the conditional distributions $P(V_i \mid \text{Parents}(V_i))$ are algorithmically independent of the marginals $P(\text{Parents}(V_i))$, because independent descriptions compress better. The algorithmic independence criterion thus falls out as a consequence of compression cost minimization — it is not a separate principle but a theorem of the framework.

## 6.3 Connection to Effective Information

Hoel, Albantakis, and Tononi's (2013) effective information (EI) measures, which Kriger (2026) cites as evidence for causal pluralism, connect naturally to PSI. EI measures the causal power of a macro-level description relative to a micro-level one. In our framework, a coarsening perturbation that *increases* PSI while maintaining or improving predictive power corresponds to a case where the macro-level description has higher EI — the macro partition captures the territory's structure more cleanly. The consumer-confidence/industrial-production merger in our macroeconomic experiment (Section 5.3) is precisely such a case.

### 6.4 Connection to Causal Abstraction

Beckers and Halpern (2019) develop a formal theory of when a high-level causal model is a faithful abstraction of a low-level one. Their consistency conditions require that interventions on macro-variables correspond to well-defined interventions on micro-variables. In our framework, PSI provides a quantitative measure of abstraction quality: a high-PSI coarsening is one where the macro-DAG is a faithful abstraction of the finer-grained DAG. This connects the perspectival account to the growing literature on causal abstraction and multi-level modeling.



### 6.5 Limitations and Open Problems

Several limitations warrant emphasis.

First, Theorem 2 assumes block-diagonal conditional independence structure. Real-world systems often have overlapping blocks, hierarchical structure, or near-independencies that are not exactly zero. Extending the theorem to approximate block structure is the most important open formal problem.

Second, our experiments use relatively moderate-dimensional datasets (9–22 variables). Scaling the perturbation analysis to high-dimensional systems (hundreds or thousands of variables) requires efficient approximations to PSI, since the number of possible perturbations grows combinatorially.

Third, we have treated the temporal ordering $\tau$ as fixed. A fuller treatment would allow $\tau$ itself to be perturbed — corresponding to observers with different temporal orientations — and study whether the thermodynamic arrow of time can be recovered as the $\tau$-maximizing PSI. Albert's (2000) Past Hypothesis and its role in grounding temporal asymmetry suggest that such a recovery should be possible for systems satisfying thermodynamic boundary conditions. We leave this as a conjecture.

Fourth, the question of how PSI behaves in highly entangled quantum systems — where the factorization assumption underlying DAG representations may break down — remains entirely open. Kriger (2026, §8) flags this as a potential boundary condition on causal modeling itself. Formalizing this boundary within our framework would require connecting PSI to measures of entanglement and non-separability, a task we defer to future work.

## 7. Conclusion

Kriger (2026) argued that causation is a compression artifact of bounded observers — real at the relational level, absent from the territory alone. The argument was philosophically compelling but formally incomplete. We have supplied the missing formalization: a compression cost functional grounded in MDL and Kolmogorov complexity, a partition stability index that quantifies causal robustness, and a theorem connecting stability-maximizing partitions to the territory's conditional independence structure. We have demonstrated empirically, on medical, economic, and physical data, that different observer partitions produce different causal graphs, that stability discriminates among them, and that the most stable graphs are the most useful for prediction and intervention.



The perspectival account of causation is now an engineering framework. It tells the practitioner not only that causal structure depends on the observer's partition, but *which* partitions to prefer and *why*. The answer is the same answer information theory has always given: prefer the partition that compresses the most, at the cost of the least.

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